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Designing and Testing HealthTracker for Activity Recognition and Energy Expenditure Estimation within the DAPHNE Platform

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Abstract

This paper describes the design and evaluation of a mobile software library, HealthTracker, which aims to produce activity and energy expenditure estimations in real-time from accelerometer and gyroscope data provided by wearable sensors. Using feature extraction together with a classifier trained using machine learning, the system will automatically and periodically send all the produced estimations to a cloud-based platform that will allow later evaluation by both the user and a physician or caretaker. The system is presented within the DAPHNE platform, an ICT ecosystem designed to provide a means for remote health and lifestyle monitoring and guidance between physicians and their patients.

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1. Introduction

In a context of growing concerns about obesity and the diseases derived from it, major importance is being placed on the role of obesity prevention by promoting a combination of a healthy and balanced diet, an active lifestyle and regular exercise. In addition, physicians are increasingly required to provide advice to their patients on how to

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achieve these goals, according to their current health parameters, medical history and physical condition. The DAPHNE platform and project (www.daphne-fp7.eu) can be defined as a response to this situation in the form of an ICT ecosystem developed to provide a means for remote personal guidance from the physicians to the users or patients in terms of health, lifestyle, exercise and nutrition.

The platform establishes a bidirectional caretaker-user remote communication based on the automatic processing of information coming from sensors worn by the user. This is done through the Aggregator mobile app, which allows this information to be periodically delivered and stored in a cloud-based solution. Nutrition information can be entered manually, either through a mobile app or a web-based interface. This web is named Personal Health System (PHS), and by accessing it users can check their own information and introduce it as well.

The physicians will access their own version of the PHS, which allows for monitoring the information about the patient, as well as providing individualized appropriate advice.

The focus of this paper is on HealthTracker, a software library integrated into the Aggregator app that produces estimations on activity and energy expenditure in real-time based on the data collected from the sensor. The HealthTracker library is designed to work with multiple commercial sensors and also with the DAPHNE sensor, designed and built specifically for the project.

The library runs on the user's mobile phone and takes as input the accelerometer and gyroscope signals delivered by the Aggregator App. Features are extracted from these signals and run through a classifier, which outputs the activity according to the features that are fed to it. Energy expenditure is then estimated based on the activity that is being performed and the physical characteristics of the user.

In section 2, we elaborate on the design process and main features of the HealthTracker library. This is followed in section 3 by an experiment carried out by the University of Leeds, which set the basis for training and tuning the system using machine learning. In section 4, the evaluation of the different features of the system is presented, leading to the conclusions in section 5.

2. HealthTracker

2.1. Activity detection

One of the main features of HealthTracker is its ability to automatically detect the physical activity performed by the user. Specifically, this system can identify six different physical activities: lying down, sitting down, standing up, walking, running and cycling. The problem can be approached as a pattern recognition problem so the usual methodology for these kind of problems will be followed. This methodology is composed of these stages:

2.1.1. Data acquisition

Motion data is collected from the sensors located at the hip and on the wrist. Six signals per sensor are obtained: linear accelerations and angular velocities in three axes captured at frequency of 100 Hz.

2.1.2. Feature extraction

Since directly classifying the raw data from sensors could be hard in terms of computational costs, the signals are analysed through temporal windows. These windows always have a fixed width of 2 seconds and a number of features are extracted from them: mean, standard deviation, median, inter-quartile range, minimum, maximum, max-min and energy.

2.1.3. Classification

In this stage the extracted features are classified to detect the physical activities performed by the users. The selected classification method was a Classification Tree (CT) because it is known that it performs well in problems of Activity Recognition and a low processing speed in comparison to other classification techniques. Since estimations are delivered to the cloud in a minute-by-minute basis but produced in time windows of 2 seconds, a majority voting process is carried out to send the predominant activity estimated during the timeframe. This also increases the robustness of the system as any possible small number of incorrect estimations will be discarded by the process.

2.1.4. System training and evaluation

In order to train the system, it is necessary to label manually the data captured from the sensors, marking the different physical activities performed by the user. Based on this labelling, the samples are divided into different classes and also into two different sets for training and testing, following a cross-validation scheme, in order to predict accuracy for future datasets.

2.2. Pedometer and distance estimation

When the type of activity detected is walking or running, the system also provides the number of steps and the distance walked by the user during the time window. The number of steps can be estimated applying a peak detection algorithm to the magnitude of the accelerometer placed at the hip. The walked distance is a function of the step frequency (number of steps divided by the time window) and the height of the user, according to this model¹:

$$s = h(a \cdot f_{\text{step}} + b) + b, \quad K = \{a, b, c\} \in R$$

Where h is the user's height, f_{step} is the step frequency and K is a set of parameters. K is determined minimizing the RMS error for a dataset in which the walking or running speed is known.

2.3. Energy expenditure estimation

Measuring the amount of energy expenditure during a time interval is crucial for the monitoring of obese patients. These estimations and the monitoring of physical activity can provide meaningful information to establish a physical profile of the patients. The Total Energy Expenditure (TEE), i.e. the total amount of energy that a person needs during a whole day, is composed by two main parts: the Resting Metabolic Rate (RMR) and the energy expended doing physical activities.

2.3.1. Energy expenditure while resting

The Resting Metabolic Rate is the amount of energy that a person spends when they are resting or sleeping. It is the lowest amount of energy that a person can spend and it corresponds to a large part of the TEE, so it is crucial to calculate it accurately. For the calculation of the RMR the users are separated into two sets: healthy people and obese adolescents. The groups are differentiated because some studies suggest that the Henry model for healthy adults is not appropriate for obese adolescents². For the healthy participants, the Henry equations³ are used to estimate the energy expenditure while for obese adolescents the Molnár equations are used because they are more accurate than the Henry ones for this particular demographic⁴.

2.3.2. Energy expenditure while performing activities

If any task other than resting is performed, the TEE will be greater than the RMR. A way to measure the relative cost of each physical activity in relation to the RMR is the Metabolic Equivalent of Task (MET). It is defined as the ratio of the metabolic rate (energy consumption) during a physical activity to a reference metabolic rate, set by

$$3.5 \frac{\text{mLO}_2}{\text{kg}} \cdot h \quad 1\text{MET} = \frac{1\text{kcal}}{\text{kg} \cdot h} \equiv 4.184 \frac{\text{kJ}}{\text{kg} \cdot h}$$

convention to

which is equivalent to:

Each activity has a standardized quantity of expended energy which can be obtained from previous works⁵. However, since the activities are divided into different levels of intensity, the MET quantities were modified in order to take into account the different intensities⁶. In addition our experiments showed that some activities were overestimated so some MET quantities were also updated based on further analysis⁷. Consequently, knowing the class of activity being done by the user and some anthropometric data, the calculation of expended energy uses the METs quantities shown in Table 1.

Table. 1 MET quantities for each activity of the DAPHNE project

Activity	Lying	Sitting	Standing	Walking	Walking	Running	Running	Cycling
Speed (km/h)	-	-	-	4	5.5	7	8	Any
METs	1	1.33	1.59	2.8	4	4.5	10	4.8

These MET tables only define a few levels of intensity (light, moderate and vigorous) for some activities such as walking or running, but the expended energy of these activities varies considerably at different speeds, and therefore a more precise method to calculate these METs quantities is proposed. Using the defined values of the METs quantities for different speeds in Jetté et al⁶, a piecewise linear interpolation function is defined for the calculation of the MET value corresponding to any speed of walking or running, shown in Figure 1.

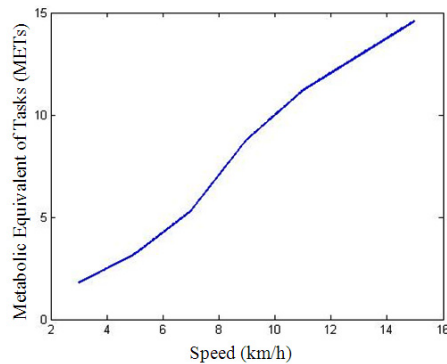


Fig. 1. MET interpolation for different walking/running speeds

3. Experimental procedure

Volunteers (18-55 year-old) were recruited from around the university campus by different researchers of the University of Leeds. 13 participants were included in the test (5 (33%) males, 8 (67%) females). Median age was 35.6 (± 11.3) years, weight 72.7 (± 17.9) kg and height 169.5 (± 8.9) cm. No volunteers were underweight, 8 (67%) were normal weight, and 5 (33%) were overweight or obese according to WHO classification. In this experiment the subjects had to perform different activities under a controlled environment, i.e. inside an indoor environment. The completion of the activities was done in the same way by all the participants. The walking/running activities were done using a treadmill and the cycling activity using a static bicycle.

The steps to complete the experiments were the following:

- The participants fill in the International Physical Activity Questionnaire (IPAQ)⁸ to show the level of physical activity that they usually do during their daily life.

- The researcher fits the two ActiGraph sensors, one at the hip and the other at the wrist of the non-dominant arm of the participant and an armband SenseWear.
- The participant lies down for a duration of 30 minutes to measure the Resting Metabolic Rate (RMR).
- The participant sits for 10 minutes.
- The participant stands still for 10 minutes.
- The participant walks on the treadmill at the pace of 4 km/h. If the participant is physically able to walk faster, the pace of walking increases to 5.5 km/h, 7 km/h and 8km/h, doing each speed in all cases for 10 minutes.
- The participant goes down from the treadmill and cycle for 10 minutes on the static bicycle.
- The sensors are turned off. The experiments are over.

Between each 10 minutes of activity the participants stood up and rested without wearing the mask (see below) for three minutes.

Resting Metabolic Rate (RMR) was measured using a GEM indirect calorimeter (GEM Nutrition, Cheshire, UK). Firstly, the GEM was calibrated using a 100% N₂ gas and secondly, using a known concentration of a mixture of CO₂, O₂, and balance N₂. RMR measurement involved participants lying supine for 30 minutes during which expired air was collected using a ventilated hood system with a one-way valve and VO₂ and VCO₂ values were sampled every 30 seconds.

Energy expenditure was measured using a Vmax Encore indirect calorimeter (Vmax Encore, Carefusion, Germany). Firstly, the Vmax was calibrated using known concentrations of 4% CO₂, 16% O₂ and 26% O₂ balanced with Nitrogen. Participants wore a facemask during the different 10 minutes periods of activity during which expired air was collected through the facemask with samples approximately every 3 seconds. Furthermore, the energy expenditure estimated by SenseWear was collected in order to compare the estimations of our system to a commercial device.

4. Evaluation

4.1. Activity classification

The objective of these tests is to check whether is possible to detect the physical activities using just one sensor and to analyse the impact that it has in the overall system. Since we have access to accelerometer and gyroscope signals, we also analyse the effect of including/excluding one or the other in the hip and wrist sensors.

The test was performed randomly splitting the training data to evaluate the expected performance of the classifier with new data using a 10-fold cross-validation scheme. The results are presented in terms of the F-Score (the harmonic mean between precision and recall) for each of these cases:

Table. 2 Classification accuracy with different signal/sensor combinations: F-scores (%)

	Signals (Wrist)	None	Accelerometer	Gyroscope	Both
Signals (Hip)	None	-	91.92	79.08	91.59
	Accelerometer	98.25	98.73	98.71	98.71
	Gyroscope	86.41	95.62	90.01	95.44
	Both	98.25	98.79	98.62	98.75

4.2. Energy expenditure while resting

Although the validity of Henry models has been proven², the measured Resting Metabolic Rates for both models (Henry and Cole) have been compared against the Indirect Calorimetry measure. The differences between the

obtained values with the gold standard technique and the predicted ones can be observed in Figure 2 (below). The relative error of the prediction was 8.72 ± 4.7 for Henry equations and 16.62 ± 10.7 for Cole equations. Therefore, it can be concluded that Henry equations are valid to estimate the Resting Metabolic Rates and they are more accurate than Cole equations.

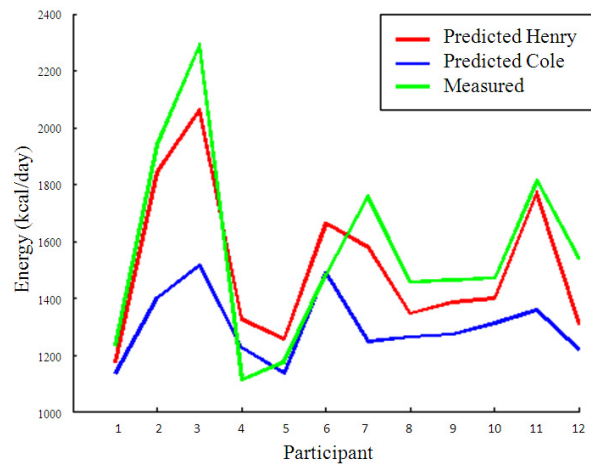


Fig. 2. Measured and predicted quantities of Resting Metabolic Rate

4.3. Energy expenditure while performing activities

The estimations provided by Sensewear has been used to compare the DAPHNE system to a commercial device with specifications stating to have an average error below 10% for measuring energy expenditure while doing free living activities. In Figure 3, the relative errors using DAPHNE are represented with box-and-whisker plots, where the quartiles of the distributions per activity are shown.

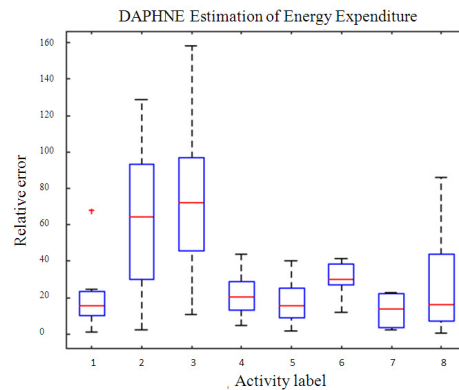


Fig. 3. Box and Whisker plot of the relative error of the DAPHNE estimates of energy expenditure

It can be observed that the accuracy of the estimation done by the Energy Expenditure system varies depending on the type of activity. The comparison between the estimations obtained by the Sensewear sensor and DAPHNE shows that they are similar achieving an average error of 29.31% for the DAPHNE sensor and 37.93% for the Sensewear solution

4.2. Pedometer

As we stated earlier, other outputs of the activity recognition system are the number of steps and the distance walked by the user. In order to evaluate them, movement data were captured while the participants were walking and running at different speeds. These activities were performed using a treadmill on which the speed was varied from 4 km/h for walking light to 8.5 km/h for running (5.5 km/h for walking moderate and 7 km/h for jogging). Therefore, these speed values obtained from the treadmill were considered as ground truth and they were compared to the walking distance (divided by the time window) provided by the activity recognition system.

Figure 4 shows the averages and standard deviations of the relative errors when estimating different walking speeds by means of the activity recognition system. It can be observed that most of the estimations are around 10% or less for walking and jogging activities and this estimation is less accurate for 8.5 km/h, however this could be expected since it corresponds to running activity which is rather different than walking activity. In spite of this higher error for running activity, the average error for all the different speeds is lower than 10% (9.99%) which may be considered as a good estimation taking into account that it is only based on the height of the user and step frequency. Although other works propose other techniques to improve the accuracy of the distance estimation⁹ using dynamic approaches instead of static ones, they require that the wearable sensor must be placed at the center of the waist and in our case the sensor was worn at the hip.

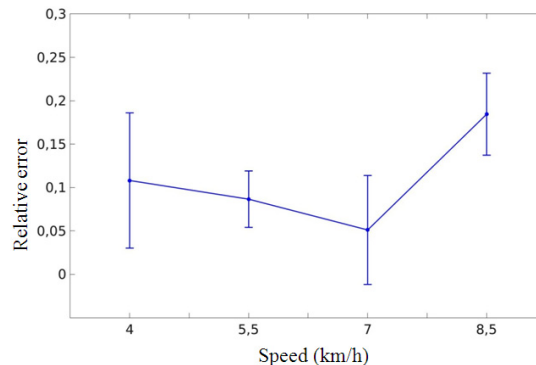


Fig. 4. Relative error of estimations of walking speeds at different speeds

5. Conclusions

The results from the activity classification tests show excellent performance (F-Score >98%) using only one sensor at the hip, with only accelerometer signals. Performance can be marginally improved (by 0.5%) by adding gyroscope signals and an additional sensor at the wrist, but we don't consider this to be cost-effective. Thus, we can state that the system is very effective in the activity classification task.

The energy expenditure estimation error is very low while resting (RMR). However, it increases to almost 30% while performing activities. Even so, we need to consider that it is lower than other solutions available on the market and that the main use for a system of this type is tracking over time the relative changes in exercise and general lifestyle conditions instead of accurately measuring energy expenditure. The pedometer's performance is also sufficient for our purposes.

We can therefore conclude that the system is very adequate for obesity prevention and tracking the lifestyle of its users, offering excellent accuracy in terms of the activity information produced throughout the day and sufficient accuracy in the cases of energy expenditure and walking length/speed estimations.

As possible lines of future work, we are currently considering improving the energy expenditure estimation feature using the amount of movement performed by the users and their physical characteristics, along with some additional parameters such as skin conductivity and heart rate.

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References

1. V.Renaudin, M. Susi and G.Lachapelle, "Step Length Estimation using Handheld Inertial Sensors" *Sensors* 2012, 12, 8507-8525
2. Hofsteenge GH, Chinapaw MJ, Delemarre-van de Waal HA, Weijs PJ, "Validation of predictive equations for resting energy expenditure in obese adolescents". *Am J Clin Nutr.* 2010 May;91(5):1244-54.
3. C. J. K. Henry and D.G.Rees, "New predictive equations for the estimation of basal metabolic rate in tropical peoples." 1991.
4. D. Molnár, S. Jeges, E. Erhardt, and Y. Schutz, "Measured and predicted resting metabolic rate in obese and nonobese adolescents.," *J. Pediatr.*, vol. 127, pp. 571–577, 1995.
5. B. E. Ainsworth, W. L. Haskell, M. C. Whitt, M. L. Irwin, a M. Swartz, S. J. Strath, W. L. O'Brien, D. R. Bassett, K. H. Schmitz, P. O. Emplancourt, D. R. Jacobs, and a S. Leon, "Compendium of physical activities: an update of activity codes and MET intensities.," *Med. Sci. Sports Exerc.*, vol. 32, no. 9 Suppl, pp. S498–504, Sep. 2000.
6. M. Jetté, K. Sidney, and G. Blümchen, "Metabolic equivalents (METS) in exercise testing, exercise prescription, and evaluation of functional capacity.," *Clin. Cardiol.*, vol. 13, no. 8, pp. 555–565, 1990.
7. M. Mansoubi, N. Pearson, S. A. Clemes, S. J. Biddle, D. H. Bodicoat, K. Tolfrey, C. L. Edwardson, and T. Yates, "Energy expenditure during common sitting and standing tasks: examining the 1.5 MET definition of sedentary behaviour," *BMC Public Health*, vol. 15, no. 1, p. 516, 2015.
8. "International Physical Activity Questionnaire (IPAQ)." URL: <https://sites.google.com/site/theipaq/cultural-adaptation>
9. Rizky Pratama A, Widyawan, Hidayat R. Smartphone-based Pedestrian Dead Reckoning as an Indoor Positioning System. *International Conference on Advanced Technologies for Communications (ATC 2014)* 2: 303-308. 2014